

# Bénéfices/risques de l'IA pour l'environnement : Que faire en contexte d'incertitude ?

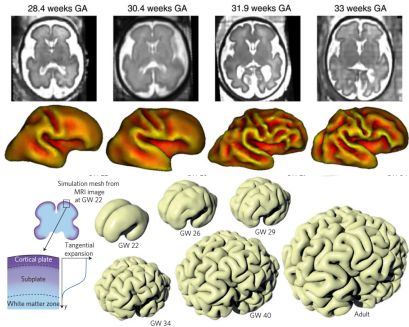
Julien Lefèvre

Aix-Marseille Université (AMU)  
julien.lefevre@univ-amu.fr

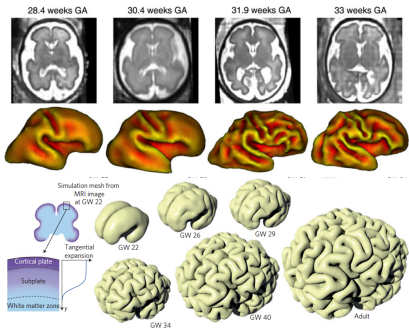
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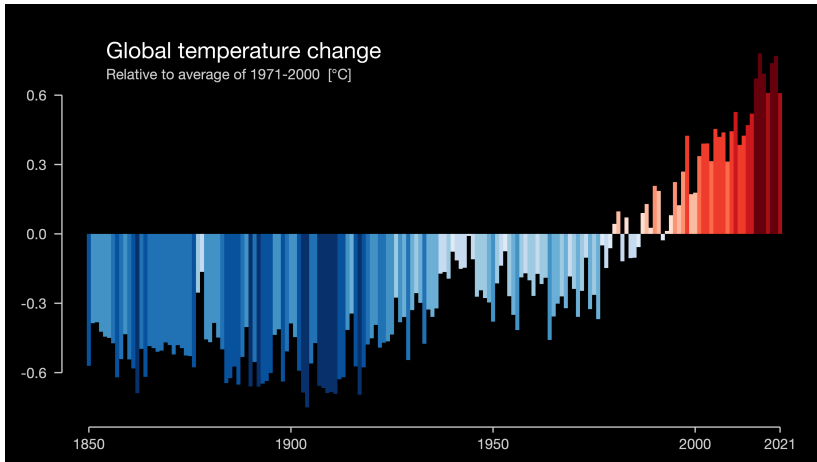


# Before and after the Satori



# Before and after the Satori





<https://showyourstripes.info/c/globe>



Article

# Unraveling the Hidden Environmental Impacts of AI Solutions for Environment Life Cycle Assessment of AI Solutions

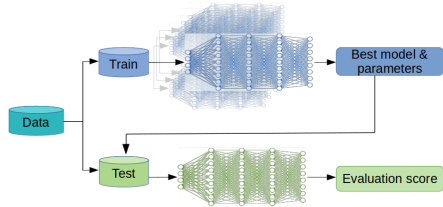
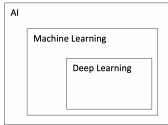
Anne-Laure Ligozat <sup>1,\*</sup>, Julien Lefevre <sup>2</sup>, Aurélie Bugeau <sup>3</sup> and Jacques Combaz <sup>4</sup>

- <sup>1</sup> Université Paris-Saclay, CNRS, ENSIE, Laboratoire Interdisciplinaire des Sciences du Numérique, 91400 Orsay, France
  - <sup>2</sup> Aix Marseille Univ, CNRS, INT, Inst Neurosci Timone, Marseille, France; julien.lefevre@univ-amu.fr
  - <sup>3</sup> Univ. Bordeaux, CNRS, Bordeaux INP, LaBRI, UMR5800, F-33400 Talence, France  
aurelie.bugeau@u-bordeaux.fr
  - <sup>4</sup> Univ. Grenoble Alpes, CNRS, Grenoble INP, VERIMAG, 38000 Grenoble, France;  
jacques.combaz@univ-grenoble-alpes.fr
- \* Correspondence: anne-laure.ligozat@lisn.upsaclay.fr

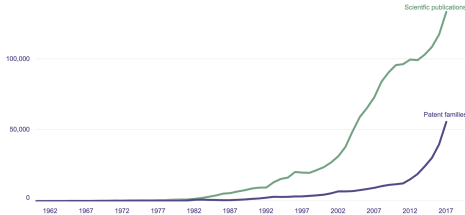
# 1 - Context

# AI

## Abuse of language



## AI growth



[WIPO Technology Trends 2019]

# AI and environment

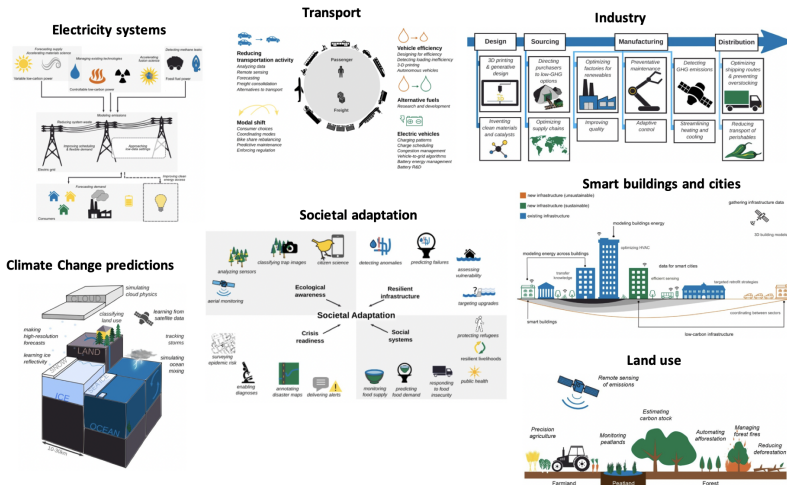
## 2 communities

- AI for green : AI as a tool for sustainable development
- green AI : measure and reduce AI impacts



# Tackling climate change with machine learning [Rolnick et al., 2019]

826 references in 13 domains



## Tackling climate change with machine learning [Rolnick et al., 2019]

Techno-optimist perspective.

But **uncertain impacts** and Jevon's paradox are mentioned :

- Transportation : *"autonomous vehicles could cause people to drive far more"*
- Industry : *"it is worth noting that greater efficiency may increase the production of goods" and thus GHG emissions"*
- Farms and forests : *"making forestry more efficient can have a negative effect by increasing the amount of wood harvested"*

## Tackling climate change with machine learning [Rolnick et al., 2019]

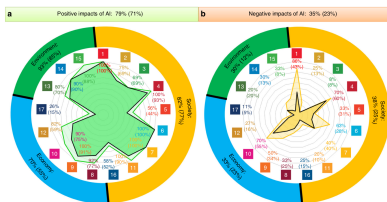
Recommendations are proposed :

*“In all these cases, projects should be pursued with great care so as not to impede or prolong the transition to a low-carbon electricity system ; ideally, projects should be **preceded by system impact analyses** to ensure that they will indeed decrease GHG emissions.”*  
p10

*“When designing and promoting new mobility services, it is important that industry and public policy prioritize lowering GHG emissions. Misaligned incentives in the early stages of technological development could result in the **lock-in to a service with high GHG emissions**”* p15

# Role of AI in achieving the Sustainable Development Goals

## 17 sustainable development goals



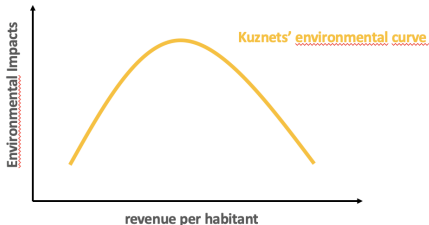
444 references for 169 goals

Some surprising aspects

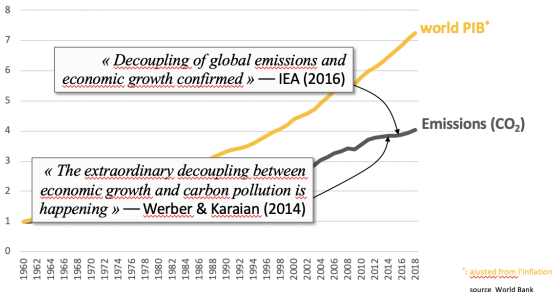
- agriculture : *"Blockchain technologies have been identified in the literature as offering potential to support vulnerable individuals and communities with affordable, secure and trusted documentation relating to rights or ownership over land"*
- energy efficiency : mostly everything is positive !

[Vinuesa et al., 2020]

# Relation with narratives on decoupling



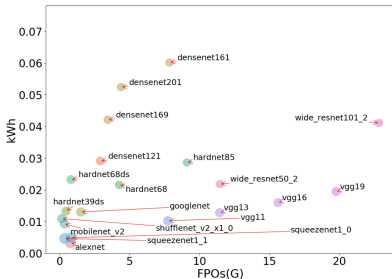
"Un peu de croissance pollue, beaucoup de croissance dépollue" - Laurence Parisot



# Measuring impacts while training (green AI)

**Method 1** : FPO (floating-point operations, i.e. number of basic operations)[Schwartz et al., 2020, Canziani et al., 2017, Henderson et al., 2020]

- Reflects the amount of calculations, Partially correlated with execution time, hardware independent
- Not completely correlated to energy consumption



## Measuring impacts while training (green AI)

### Method 2 : Measuring energy use

[Schwartz et al., 2020, Canziani et al., 2017]

$$E_{total} = PUE (E_{dram} + E_{cpu} + E_{gpu})$$

then convert it to CO2e

$$CO2e = EmissionFactor * E_{total}$$

# Some existing tools

**Machine Learning Emissions Calculator**

Choose your hardware, runtime and cloud provider to estimate the carbon impact of your research.

This calculator will give you 3 numbers: the raw carbon-emissions produced and the emissions after carbon emissions. The carbon footprint depends on the GPU used and the cloud provider you use as a variable. Update our website if anything has changed or is outdated.

Hardware type:  Model:  Provider:  Region of Computation:

Carbon footprint: **14** kg CO<sub>2</sub>eq

14 kg of CO<sub>2</sub>eq is equivalent to:  
36.4 kWh of energy per average US home | 0.66 kg of coal burned | 0.66 tree seedlings needed to offset for 10 years

**Publish**

We believe that an important step towards reducing carbon emissions is the generalization of emissions reporting in papers, blog posts and publications in general.

To that end, here is a LaTeX template you can use in your publications to report the emissions you have calculated with this Calculator.

Generated LaTeX Template

```
documentclass{article}
\documentstyle{IEEEtran}
\begin{document}
\begin{figure}


```

**Green Algorithms**  
How green are your computations?

**CO<sub>2</sub>** 303.10 g CO<sub>2</sub>e  
Carbon footprint

**⚡** 2.28 kWh  
Energy needed

**🌳** 0.33 tree-months  
Carbon sequestration

**🚗** 1.73 km  
in a passenger car

**✈️** 1%  
of a flight Paris-London

Share your results with [this link](#)

**Details about your algorithm**

To understand how each parameter impacts your carbon footprint, check out the formula below and the [maths on this](#).

Runtime (H:MM:SS)

Type of cores:

Number of cores:

Model:

Memory available (in GB):

Select the platform used for the computations:

Select location:  
Europe  
Asia

Do you know the real usage factor of your CPU?  
 Yes  No

Do you know the Power Usage Efficiency (PUE) of your local data centre?  
 Yes  No

Do you want to use a Pragmatic Scaling Factor?  
 Yes  No

**Computing cores VS Memory**

**How the location impacts your footprint**

Bar chart showing emissions (gCO<sub>2</sub>e) for different locations: Paris, London, New York, Tokyo, Sydney, Melbourne, Sao Paulo, Bangalore, Mumbai, Delhi, Beijing, Shanghai, Hong Kong, Singapore, Seoul, Taipei, Sydney, Melbourne, Sao Paulo, Bangalore, Mumbai, Delhi, Beijing, Shanghai, Hong Kong, Singapore, Seoul, Taipei.

<http://www.green-algorithms.org/>

<https://mlco2.github.io/impact/>

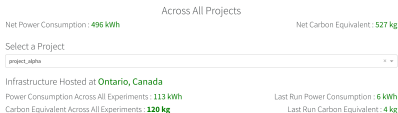


# Some existing tools : code

## codecarbon (mlco2)

```
from codecarbon import EmissionsTracker

tracker = EmissionsTracker()
tracker.start()
# GPU Intensive code goes here
tracker.stop()
```



### Exemplary Equivalents



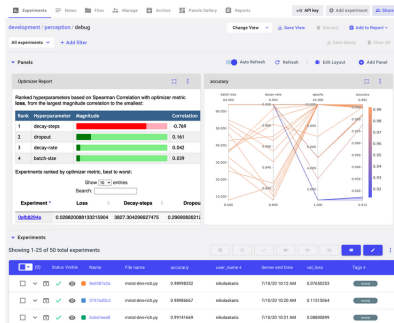
74.73 %  
of weekly  
American  
household  
emissions



293 miles  
driven



52 days  
of 32-inch  
LCD TV  
watched



## Some results

- 4 NLP models (natural language processing) [Strubell et al., 2019]
- Estimated energy consumption while training

Model	Hardware	Power (W)	Hours	kWh-PUE	CO <sub>2</sub> e	Cloud compute cost
Transformer <sub>base</sub>	P100x8	1415.78	12	27	26	\$41–\$140
Transformer <sub>big</sub>	P100x8	1515.43	84	201	192	\$289–\$981
ELMo	P100x3	517.66	336	275	262	\$433–\$1472
BERT <sub>base</sub>	V100x64	12,041.51	79	1507	438	\$3751–\$12,571
BERT <sub>base</sub>	TPUv2x16	—	96	—	—	\$2074–\$6912
NAS	P100x8	1515.43	274,120	656,347	626,155	\$942,973–\$3,201,722
NAS	TPUv2x1	—	32,623	—	—	\$44,055–\$146,848
GPT-2	TPUv3x32	—	168	—	—	\$12,902–\$43,008

Most widely used model at the time  
652 kg CO<sub>2</sub>e  
~1 round-trip Paris Hong Kong by plane  
or ~2 500km en voiture

PUE = 1.58 (Ascierto, 2018)  
FE = 0.954

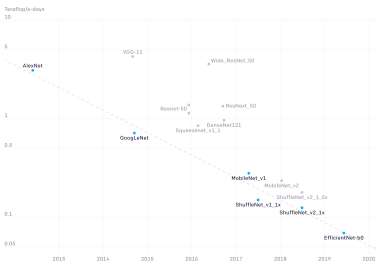
### Conclusions from authors

- Need for cost-resource/accuracy analysis
- Public and shared computing resources for academics (price)
- Development of less consuming hardware and algorithms

# Limits of existing works

- AI community not well aware of existing works on impacts
- Mono-criterion
- Perimeter : electricity consumption during training
- Promises

64x less compute required to get to AlexNet performance 7 years later (log scale)



## The Carbon Footprint of Machine Learning Training Will Plateau, Then Shrink

David Patterson<sup>1,2</sup>, Joseph Gonzalez<sup>2</sup>, Urs Hölzle<sup>1</sup>, Quoc Le<sup>1</sup>, Chen Liang<sup>1</sup>, Lluís-Miquel Munguia<sup>1</sup>, Daniel Rothchild<sup>2</sup>, David So<sup>1</sup>, Maud Texier<sup>1</sup>, and Jeff Dean<sup>1</sup>

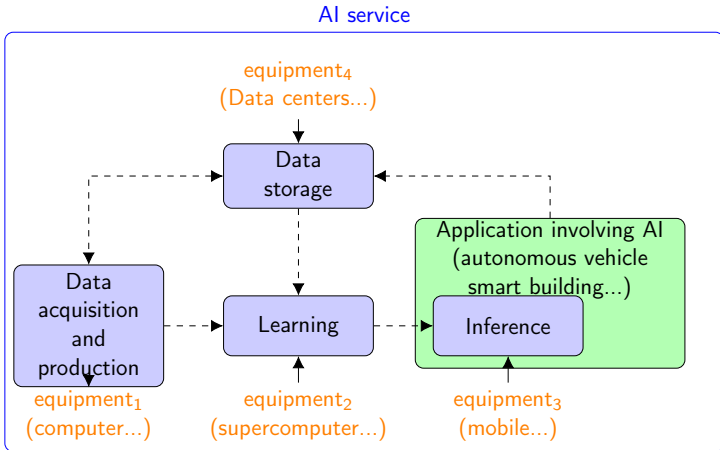
**Abstract:** Machine Learning (ML) workloads have rapidly grown in importance, but raised concerns about their carbon footprint. Four best practices can reduce ML training energy by up to 100x and CO<sub>2</sub> emissions up to 1000x. By following best practices, overall ML energy use (across research, development, and production) held steady at <15% of Google's total energy use for the past three years. If the whole ML field were to adopt best practices, total carbon emissions from training would reduce. Hence, we recommend that ML papers include emissions explicitly to foster competition on more than just model quality. Estimates of emissions in papers that omitted them have been off 100x–100,000x, so publishing emissions has the added benefit of ensuring accurate accounting. Given the importance of climate change, we must get the numbers right to make certain that we work on its biggest challenges.

## Reducing AI impacts (green AI)

- Reduce number of parameters of neural networks, size of datasets, etc
- Frugal / sober AI → 24th-25th November in Grenoble
- Dismantle AI [Couillet 2022]

2 - How to evaluate AI services dedicated to environment ?

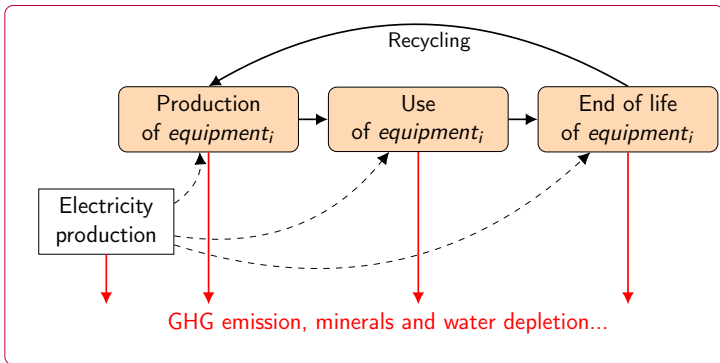
# Lifecycle of an AI service



## Environmental impacts of a service

The lifecycle assessment (LCA) of a service relies on :

- LCAs of the equipments/devices involved in the service
- allocation procedures (keys) to determine the fraction of the impacts attributed to the service.



Life cycle assessment (LCA) of an equipment

## Environmental benefits of an AI solution

The (potential) benefits of an AI solution  $M_2$  which is a substitute for a reference solution  $M_1$  (typically without AI) are deduced from a comparative LCA :

$$\Delta(M_2|M_1) = LCA(M_2) - LCA(M_1) \in \mathbb{R}^d \quad (1)$$

Common pitfalls in such evaluations :

- focusing on a single environmental criterion (burden shift)
- restricted perimeter
- generalization of contextual solutions/benefits
- third-order effects (e.g. rebound effects) are overlooked.



## Example : a smart-building

Commonly overlooked aspects :

- lifecycle impacts of devices (sensors, DC, networks, ...)
- impacts of the training phase
- what are the impacts of the smart solution(s) on the design of the building?
- are claimed energy gains reliable in the operational context?
- is the solution(s) applicable to old buildings?
- human interactions : rebound effects, counteracting behaviors.

### 3 - Literature study

# Is AI for green aware of its own impact ?

If yes, how is it measured ?

Do the authors are able to say that a new solution is better than an old one ?

	Causal inference	Computer vision	Interpretable models	NLP	RL & Control	Time-series analysis	Transfer learning	Uncertainty quantification	Unsupervised learning
<b>Electricity systems</b>									
Enabling low-carbon electricity	•	•			•	•		•	•
Reducing current-system impacts									•
Ensuring global impact							•		•
<b>Transportation</b>									
Reducing transport activity						•		•	
Improving vehicle efficiency					•				
Alternative fuels & electrification									•
Modal shift	•	•						•	
<b>Buildings and cities</b>									
Optimizing buildings	•				•	•			
Urban planning		•					•		•
The future of cities				•				•	•
<b>Industry</b>									
Optimizing supply chains		•			•	•			
Improving materials									•
Production & energy		•	•						
<b>Farms &amp; forests</b>									
Remote sensing of emissions		•							
Precision agriculture		•				•	•		
Monitoring peatlands		•							
Managing forests		•				•	•		
<b>Carbon dioxide removal</b>									
Direct air capture								•	•
Sequestering CO <sub>2</sub>		•							

[Rolnick et al., 2019]

	Climate prediction	Societal impacts	Solar geoengineering	Individual action	Collective decisions	Education	Finance
<b>Adaptation</b>							
Uniting data, ML & climate science	•	•					•
Forecasting extreme events	•	•					•
<b>Societal impacts</b>							
Ecology		•					
Infrastructure						•	•
Social systems		•				•	•
Crisis		•					
<b>Solar geoengineering</b>							
Understanding & improving aerosols						•	•
Engineering a control system						•	•
Modeling impacts						•	•
<b>Individual action</b>							
Understanding personal footprint				•		•	•
Facilitating behavior change						•	•
<b>Collective decisions</b>							
Modeling social interactions					•		
Informing policy				•			
Designing markets						•	•
<b>Education</b>							
Finance						•	•

## Case studies

Analysis of several domains in [Rolnick et al., 2019] identified with "high leverage" (Modelling demand/freight, Electric vehicle, Low carbon, Smart buildings).

57 articles have an environmental evaluation following the categories :

- a No mention of the environmental gain.
- b General mention of the environmental gain.
- c No quantitative evaluation or only indirect estimation.
- d Evaluation of the energy gain without the AI program.
- e Evaluation of the energy gain taking the use phase of the AI service into account.
- f Comprehensive evaluation of the environmental gain (comparison of LCAs).

# A few examples

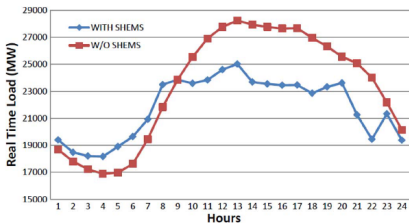
Guess which category ! :-)

1878

IEEE TRANSACTIONS ON SMART GRID, VOL. 4, NO. 4, DECEMBER 2013

## Hardware Design of Smart Home Energy Management System With Dynamic Price Response

Qinran Hu, Student Member, IEEE, and Fangxing Li, Senior Member, IEEE

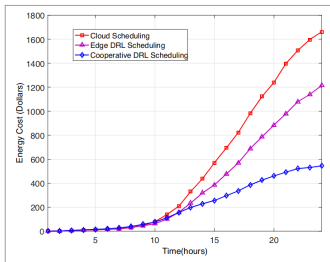


ML methods : Bayes classifier, Hidden Markov Model

INTERNET OF THINGS FOR SMART CITIES: TECHNOLOGIES AND APPLICATIONS

## Intelligent Edge Computing for IoT-Based Energy Management in Smart Cities

Yi Liu, Chao Yang, Li Jiang, Shengli Xie, and Yan Zhang



Deep Learning

# A few examples

Guess which category ! :-)



## ARTIFICIAL INTELLIGENCE IN LOGISTICS

A collaborative report by DHL and IBM on implications  
and use cases for the logistics industry

2018

Powered by DHL, Next Research

### 1.3 Trends Accelerating AI

Core technological advances are central to the continued development of AI. Significant progress has been made with all core AI technologies, and the levels of investment and demand for ongoing improvement give good reason to expect this growth will continue well into the future. Technological advances can be classified into three broad categories: improving computer processing speed and power; increasing AI system access to big data, and using algorithmic improvements to enable more complex AI applications.

**Computing Power & Speed:** AI is a computer processing intensive technology – breakthroughs in computing power and efficiency have enabled the expansion and complexity of AI applications. In the technology industry, Moore's Law is used to show the relationship between the cost and speed of computer processing power over time, the trajectory of which results in an exponential curve as seen in Figure 12. Until recently, a computing device's CPU, or central processing unit, typically provided the core function of processing. In recent years, GPUs, or graphical processing units, have begun to partially take over computer processing workload, contributing significantly to the rise of AI.

Originally designed for the much larger and more complex computational workloads of rendering computer gaming graphics in real time, GPUs are designed to handle hundreds of tasks in parallel, and today are successfully being used to enable AI applications.

Advances in computer chip technology are an important part of the AI developmental story. Given the consistency of chip improvements and the likelihood that chip design will continue to improve, this is not the primary reason for the existence of AI but just one of the essential enablers.

#### THE DIFFERENCE BETWEEN A CPU AND GPU

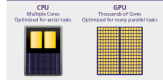


Figure 11: Comparison of CPUs and GPUs. Source: Nvidia

#### LAW OF ACCELERATING RETURNS

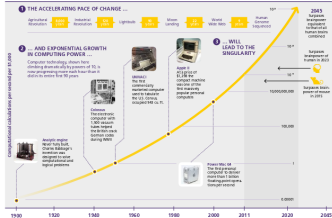


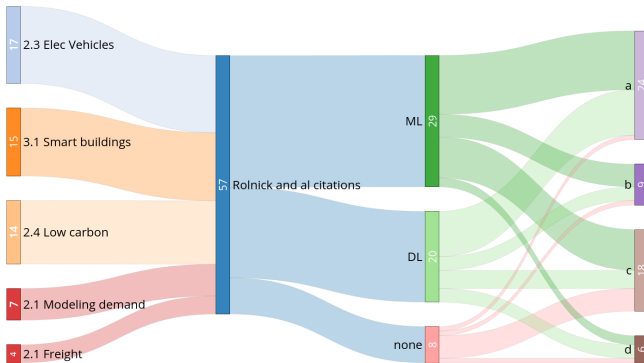
Figure 12: Ray Kurzweil's Law of Accelerating Returns depicts the exponential growth of computer processing power and technology innovations throughout history, and anticipates computers will exceed human intelligence in the future. Source: TIME / Wikipedia

## Main result

**We found no studies that follow the categories :**

- e Evaluation of the energy gain taking the use phase of the AI service into account.
- f Comprehensive evaluation of the environmental gain (comparison of LCAs).

# How to evaluate AI services dedicated to environment?



- a No mention of the environmental gain.
- b General mention of the environmental gain.
- c No quantitative evaluation or only indirect estimation.
- d Evaluation of the energy gain without the AI program.



## To summarize

- Framework to evaluate the direct impacts of AI for green applications
- The analysis of literature on AI has raised several issues

## Discussion

- Current Environmental Evaluation of AI Services is Under-Estimated (mostly energy/GHG)
- Many unknowns in the LCA (e.g. production of GPU)  
=> *AI community should lobby the companies to open a part of their data*
- Large structural changes (Third-order effects) are difficult to take into account e.g through the IoT whose large deployment may impact material demand (Lithium, Cobalt...)  
=> *Consequential LCA instead of attributional LCA*
- Narratives about dematerialization and techno-solutionism  
=> *Many scientists question techno-solutionism as the only answer to the environmental emergency.*  
=> *The promises suggested by these new technologies should be more debated.*

# 4 - Remise en perspective

## Que faire, en contexte d'incertitudes ?

### "Que faire ?"

- Question récurrente, au niveau des individus, après une prise de conscience écologique.
- Question a priori moins habituelle dans l'ESR où créer et transmettre du savoir n'est pas toujours perçu comme relevant d'un "faire".
- Fondement même de la politique (*politikos/politeia*)

La question peut être abordée au travers des différent.e.s acteurs.rices impliqué.e.s : décideurs, industriels, scientifiques, citoyen.ne.s. (inspiration [atelier SEnS](#))

On reste dans le cadre du numérique en élargissant un peu la perspective (risques sociétaux, démocratiques etc).

## 4 - Remise en perspective

Agir du point du/de la citoyen.ne

- Ecogestes
- Sobriété
- Boycott

Selon [carbone4](#), les actions individuelles vertueuses pourraient conduire à une réduction d'un quart des émissions GES.

## 4 - Remise en perspective

### Agir du point de vue des décideurs

- Rapports en amont, exemples : [rapport Villani \(2018\)](#), [rapport IoT \(2022\)](#)
- Autorités de régulation (ARCEP)
- Feuille de route du numérique (2021)
- Loi REEN (2021)

Innovation politique via la convention citoyenne pour le climat et le moratoire sur la 5G.

## 4 - Remise en perspective

### Agir du point de vue des industriels

- Contraintes de rentabilité économique
- Ecueil du greenwashing, via le discours sur l'efficacité
- Lobbying hasardeux (exemple : le Metavers et ses bénéfices sur l'environnement)

**Moratoire** pour proposer une pause sur l'apprentissage d'IA géante.

## 4 - Remise en perspective

### Agir du point de vue de la/du scientifique

- Utiliser ses compétences pour développer des projets de recherche en lien avec l'écologie (risque de greenwashing).
- Compte tenu de l'incertitude sur les impacts de l'IA/du numérique, aller vers plus d'études ou d'analyses pour permettre une meilleure quantification (labos1point5, ecoinfo).

Proposer des recommandations (exemple : document de cadrage Évaluation environnementale de projets impliquant des méthodes d'IA par ecoinfo)



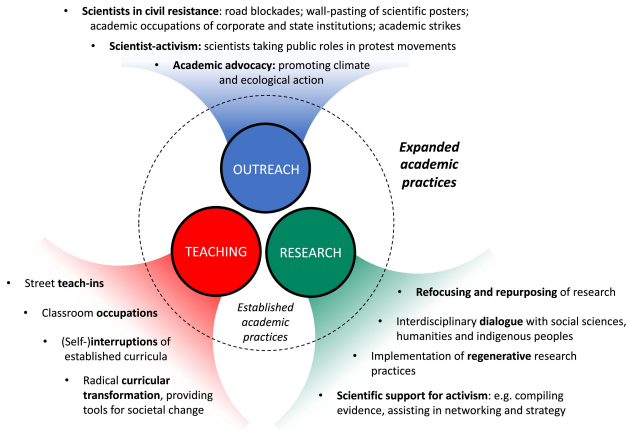
## 4 - Remise en perspective

### Agir avec reflexivité

- La production, d'artefacts ou même de connaissances s'inscrit dans un tissu d'act.eur.rice.s, avec des dépendances, des rapports de force, des discours etc
- Prendre conscience de cet écosystème, l'étudier et en tirer un discours critique fait partie d'une activité réflexive
- C'est un des sujets d'intérêt des atecopols (Toulouse, Paris, Marseille etc)

En parallèle et en lien avec un renouveau de la pensée techno-critique des années 70 (Ellul, Illich, Gorz...) avec du sang neuf (F. Jarrige, J.B. Fressoz, A. Monnin, F. Lopez...)

# Diversité des formes d'action



[Racimo et al., 2022]

# Pour finir : Un projet réflexif ?

## What Neuroscience in the Anthropocene era ?



### Objectives



#### Global aim

Entrain the NeuroMarseille community to an environmentally responsible research

#### Specific aims

- redefining neuroscientific questions for understanding the actual crisis (WP1)
- interdisciplinary meetings on neuroscience at the era of anthropocene (WP2)
- adopting a sociological vision on shared values, unthought and wills for the future of the community with respect to the climate crisis (WP2)
- identifying, sharing and promoting existing virtuous practices and evaluation of the impact of neuroscientific research. Improving scientific practices (WP3).
- Endorsement by UNESCO: International Year of Basic Sciences for Sustainable Development.



# References I



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